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13. ABSTRACT *(Maximum 200 words)*
During the second year of the DARPA ANNT Program contact, new neural network architectures were developed to carry out autonomous real-time preprocessing, segmentation, recognition, timing, and control of both spatial and temporal inputs. These architectures contribute to: (1) preprocessing of visual form and motion signals; (2) preprocessing of acoustic signals; (3) adaptive pattern recognition and categorization in an unsupervised learning context; (4) adaptive pattern recognition and prediction in a supervised learning context; (5) processing of temporal patterns using working memory networks, with applications to 3-D object recognition; (6) adaptive timing for task scheduling; (7) adaptive sensory-motor control using head-centered spatial representations of 3-D target position.

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DEVELOPMENT OF NEURAL NETWORK ARCHITECTURES FOR SELF-ORGANIZING PATTERN RECOGNITION AND ROBOTICS

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Development of Neural Network Architectures
for Self-Organizing Pattern Recognition and Robotics

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Development of Neural Network Architectures for Self-Organizing Pattern Recognition and Robotics

Contract AFOSR 90-0083 (Year 2)

Principal Investigators:
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SUMMARY

During the second year of the DARPA ANNT Program contract, new neural network architectures were developed to carry out autonomous real-time preprocessing, segmentation, recognition, timing, and control of both spatial and temporal inputs. Brief summaries are followed by more extensive ones.

(1) Preprocessing of visual form and motion signals: Parallel cortical systems for the processing of static visual forms and moving visual forms are derived from a principle called FM Symmetry. A feedforward What-and-Where filter models parallel visual systems to generate an input representation (What it is) that is invariant to position, size, and orientation without discarding this information (Where it is). Synchronized oscillations in a model of visual cortex are capable of rapidly binding spatially distributed feature detectors into a globally coherent segmentation. The vision model is also applied to the processing of synthetic aperture radar (SAR) images.

(2) Preprocessing of acoustic signals: A neural network model for preprocessing of an acoustic source generates a representation of pitch as a spatial pattern that emerges from a type of neural *harmonic sieve*.

(3) Adaptive pattern recognition and categorization: Unsupervised learning: A new analog adaptive resonance model (Fuzzy ART) incorporates computations from fuzzy set theory into the binary ART 1 model. When used as part of a larger architecture for supervised learning, Fuzzy ART enables the user to interpret vectors of learned adaptive weights as if-then rules, thus defining a self-organizing expert system.

(4) Adaptive pattern recognition and prediction: Supervised learning: The Fuzzy ARTMAP architecture carries out incremental supervised learning of recognition categories and multidimensional maps in response to arbitrary sequences of analog or binary vectors. A Minimax Learning Rule conjointly minimizes predictive error and maximizes code compression, thereby optimally shaping recognition categories to the statistics of the input environment. Benchmark studies affirm Fuzzy ARTMAP's power compared to alternative models from machine learning, genetic algorithms, and neural networks, including application domains such as large database analysis. Another system (NEXsT) uses VLSI switching theory to design neural networks with a minimum number of if-then rules for binary supervised learning problems.

(5) Temporal patterns, working memory, and 3-D object recognition: Working memory neural networks, called Sustained Temporal Order REcurrent (STORE) models, encode the invariant temporal order of sequential events, with repeated or non-repeated items, in a manner that is stable under incremental learning conditions.

(6) Adaptive timing: A new network circuit models adaptive timing of recognition and reinforcement learning. The model is closely linked to circuits in the hippocampus.

(7) Adaptive control: A model of sensory-motor control shows how outflow eye movement commands can be transformed by two stages of opponent processing into a head-centered spatial representation of 3-D target position. Opponent processing is again a key

element in an analysis of arm movement data. Related model properties are used in an application to optimal control of machine set-up scheduling.

These and related projects, including model development, analysis, simulation, and comparisons with behavioral and neural data, are described below.

The contract provided partial summer salary for the two Principal Investigators and supported four Research Assistants, all of whom are PhD students in the Boston University Department of Cognitive and Neural Systems.

1. PREPROCESSING OF VISUAL FORM AND MOTION SIGNALS

(A) Why Do Parallel Cortical Systems Exist for the Perception of Static Form and Moving Form?

This project analyses computational properties that clarify why the parallel cortical systems $V1 \rightarrow V2$, $V1 \rightarrow MT$, and $V1 \rightarrow V2 \rightarrow MT$ exist for the perceptual processing of static visual forms and moving visual forms. A symmetry principle, called FM Symmetry, is predicted to govern the development of these parallel cortical systems by computing all possible ways of symmetrically gating sustained cells with transient cells and organizing these sustained-transient cells into opponent pairs of on-cells and off-cells whose output signals are insensitive to direction-of-contrast. This symmetric organization explains how the static form system (Static BCS) generates emergent boundary segmentations whose outputs are insensitive to direction-of-contrast and insensitive to direction-of-motion, whereas the motion form system (Motion BCS) generates emergent boundary segmentations whose outputs are insensitive to direction-of-contrast but sensitive to direction-of-motion. FM Symmetry clarifies why the geometries of static and motion form perception differ; for example, why the opposite orientation of vertical is horizontal (90°), but the opposite direction of up is down (180°). Opposite orientations and directions are embedded in gated dipole opponent processes that are capable of antagonistic rebound. Negative afterimages, such as the MacKay and waterfall illusions, are hereby explained, as are aftereffects of long-range apparent motion. These antagonistic rebounds help to control a dynamic balance between complementary perceptual states of resonance and reset. Resonance cooperatively links features into emergent boundary segmentations via positive feedback in a CC Loop, and reset terminates a resonance when the image changes, thereby preventing massive smearing of percepts. These complementary preattentive states of resonance and reset are related to analogous states that govern attentive feature integration, learning, and memory search in Adaptive Resonance Theory. The mechanism used in the $V1 \rightarrow MT$ system to generate a wave of apparent motion between discrete flashes may also be used in other cortical systems to generate spatial shifts of attention. The theory suggests how the $V1 \rightarrow V2 \rightarrow MT$ cortical stream helps to compute moving-form-in-depth and how long-range apparent motion of illusory contours occurs. These results collectively argue against vision theories that espouse independent processing modules. Instead, specialized subsystems interact to overcome computational uncertainties and complementary deficiencies, to cooperatively bind features into context-sensitive resonances, and to realize symmetry principles that are predicted to govern the development of visual cortex. [35–58]

(B) Cortical Dynamics of Visual Motion Perception: Short-Range and Long-Range Apparent Motion

The theory of biological motion perception is also used to explain classical and recent data about short-range and long-range apparent motion percepts that have not yet been explained by alternative models. These data include beta motion; split motion; gamma motion and reverse-contrast gamma motion; delta motion; visual inertia; the transition from group motion to element motion in response to a Ternus display as the interstimulus interval (ISI) decreases; group motion in response to a reverse-contrast Ternus display even at short ISIs; speed-up of motion velocity as interflash distance increases or flash duration decreases; dependence of the transition from element motion to group motion on stimulus duration and size; various classical dependencies between flash duration, spatial separation, ISI, and motion threshold known as Korte's Laws; dependence of motion strength on stimulus orientation and spatial frequency; short-range and long-range form-color interactions; and binocular interactions of flashes to different eyes. [41, 42]

(C) A What-and-Where Neural Network for Invariant Image Preprocessing

The What-and-Where filter is a feedforward neural network for invariant image preprocessing that represents the position, orientation, and size of an image figure (where it is) in a multiplexed spatial map. This map is used to generate an invariant representation of the figure that is insensitive to position, orientation, and size for purposes of pattern recognition (what it is). A multiscale array of oriented filters, followed by competition between orientations and scales is used to define the Where filter. [14]

(D) Synchronized Oscillations during Cooperative Feature Linking in a Cortical Model of Visual Perception

A neural network model of synchronized oscillator activity in visual cortex accounts for recent neurophysiological findings that such synchronization may reflect global properties of the stimulus. In these recent experiments, it was reported that synchronization of oscillatory firing responses to moving bar stimuli occurred not only for nearby neurons, but also occurred between neurons separated by several cortical columns (several *mm* of cortex) when these neurons shared some receptive field preferences specific to the stimuli. These results were obtained not only for single bar stimuli but also across two disconnected, but colinear, bars moving in the same direction. Computer simulations of the synchronized oscillator obtain these synchrony results across both single and double bar stimuli. For the double bar case, synchronous oscillations are induced in the region between the bars, but no oscillations are induced in the regions beyond the stimuli. These results were achieved with cellular units that exhibit limit cycle oscillations for a robust range of input values, but which approach an equilibrium state when undriven. Single and double bar synchronization of these oscillators was achieved by different, but formally related, models of preattentive visual boundary segmentation and attentive visual object recognition, as well as nearest-neighbor and randomly coupled models. In preattentive visual segmentation, synchronous oscillations may reflect the binding of local feature detectors into a *globally coherent grouping*. In object recognition, synchronous oscillations may occur during an attentive resonant state that triggers new learning. These modelling results support earlier theoretical predictions of synchronous visual cortical oscillations and demonstrate the robustness of the mechanisms capable of generating synchrony. [43–45]

(E) Processing of Synthetic Aperture Radar Images by the Boundary Contour System and Feature Contour System

An improved Boundary Contour System (BCS) and Feature Contour System (FCS) neural network model of preattentive vision has been applied to two large images containing range data gathered by a synthetic aperture radar (SAR) sensor. The goal of processing is to make structures such as motor vehicles, road, or buildings more salient and more interpretable to human observers than they are in the original imagery. Early processing by shunting center-surround networks compresses signal dynamic range and performs local contrast enhancement. Susequent processing by filters sensitive to oriented contrast, including short-range competition and long-range cooperation, segments the image into regions. Finally, a diffusive filling-in operation within the segmented regions produces coherent visible structures. The combination of BCS and FCS helps to locate and enhance structure over regions of many pixels, without the resulting blur characteristic of approaches based on low spatial frequency filtering alone. [29]

2. PREPROCESSING OF ACOUSTIC SIGNALS

(A) A Neural Network for Synthesizing the Pitch of an Acoustic Source

A neural network model capable of generating a spatial representation of the pitch of an acoustic source has been developed. Pitch is one of several auditory percepts used by humans to separate multiple sound sources in the environment from each other. The model provides a neural instantiation of a type of "harmonic sieve." It is capable of quantitatively simulating a large body of psychoacoustical data, including new data on octave shift perception. [28]

3. ADAPTIVE PATTERN RECOGNITION AND CATEGORIZATION: UNSUPERVISED LEARNING

(A) Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System

A fuzzy Adaptive Resonance Theory (ART) model capable of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary input patterns has been developed. Fuzzy ART incorporates computations from fuzzy set theory into the ART 1 neural network, which learns to categorize only binary input patterns. The generalization to learning both analog and binary input patterns is achieved by replacing appearances of the intersection operator ($\cap$) in ART 1 by the MIN operator ($\wedge$) of fuzzy set theory. The MIN operator reduces to the intersection operator in the binary case. Category proliferation is prevented by normalizing input vectors at a preprocessing stage. A normalization procedure called complement coding leads to a symmetric theory in which the MIN operator ($\wedge$) and the MAX operator ($\vee$) of fuzzy set theory play complementary roles. Complement coding uses on-cells and off-cells to represent the input pattern, and preserves individual feature amplitudes while normalizing the total on-cell/off-cell vector. Learning is stable because all adaptive weights can only decrease in time. Decreasing weights correspond to increasing sizes of category "boxes". Smaller vigilance values lead to larger category boxes. Learning stops when the input space is covered by boxes. With fast learning and a finite input set of arbitrary size and composition, learning stabilizes after just one presentation of each input pattern. A fast-commit slow-recode option combines fast learning with a forgetting rule that buffers system memory against noise. Using this option, rare events can be rapidly learned, yet previously learned memories are not rapidly erased in response to statistically unreliable input fluctuations. [26, 27]

4. ADAPTIVE PATTERN RECOGNITION AND PREDICTION: SUPERVISED LEARNING

(A) Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps

A new neural network architecture carries out incremental supervised learning of recognition categories and multidimensional maps in response to arbitrary sequences of analog or binary input vectors. The architecture, called Fuzzy ARTMAP, achieves a synthesis of fuzzy logic and Adaptive Resonance Theory (ART) neural networks by exploiting a close formal similarity between the computations of fuzzy subsethood and ART category choice, resonance, and learning. Fuzzy ARTMAP also realizes a new Minimax Learning Rule that conjointly minimizes predictive error and maximizes code compression, or generalization. This is achieved by a match tracking process that increases the ART vigilance parameter by the minimum amount needed to correct a predictive error. As a result, the system automatically learns a minimal number of recognition categories, or "hidden units", to meet accuracy criteria. Category proliferation is prevented by normalizing input vectors at a preprocessing stage. A normalization procedure called complement coding leads to a symmetric theory in which the AND operator ($\wedge$) and the OR operator ($\vee$) of fuzzy logic play complementary roles. Complement coding uses on-cells and off-cells to represent the input pattern, and preserves individual feature amplitudes while normalizing the total on-cell/off-cell vector. Learning is stable because all adaptive weights can only decrease in time. Decreasing weights correspond to increasing sizes of category "boxes". Smaller vigilance values lead to larger category boxes. Improved prediction is achieved by training the system several times using different orderings of the input set. This voting strategy can also be used to assign confidence estimates to competing predictions given small, noisy, or incomplete training sets. Four classes of simulations illustrate Fuzzy ARTMAP performance as compared to benchmark back propagation and genetic algorithm systems. These simulations include (i) finding points inside vs. outside a circle; (ii) learning to tell two spirals apart; (iii) incremental approximation of a piecewise continuous function; and (iv) a letter recognition database. The Fuzzy ARTMAP system is also compared to Salzberg's NGE system and to Simpson's FMMC system. [12, 15–18]

(B) Comparative Performance Measures of Fuzzy ARTMAP, Learned Vector Quantization, and Back Propagation for Handwritten Character Recognition

A simulation study compares the performance of Fuzzy ARTMAP with that of Learned Vector Quantization and Back Propagation on a handwritten character recognition task. Training with Fuzzy ARTMAP to a fixed criterion used many fewer epochs. Voting with Fuzzy ARTMAP yielded the highest recognition rates. [13]

(C) Construction of Neural Network Expert Systems using Switching Theory

This project introduces a new family of neural network architectures (NEXsT) that use switching theory to construct and train minimal neural network classification expert systems. The primary insight that leads to the use of switching theory is that the problem of minimizing the number of rules and the number of IF statements (antecedents) per rule in a neural network expert system can be recast into the problem of minimizing the number of digital gates and the number of connections between digital gates in a Very Large Scale Integrated (VLSI) circuit. Algorithms for minimizing the number of gates and the number of connections between gates in VLSI circuits are used, with some modification, to generate minimal neural network classification expert systems. The minimal set of rules that the neural network generates to perform a task are readily extractable from the network's weights and topology. Analysis and simulations on several databases illustrate the system's performance. [48]

5. TEMPORAL PATTERNS, WORKING MEMORY, AND 3-D OBJECT RECOGNITION

(A) Working Memory Networks for Learning Temporal Order with Application to 3-D Visual Object Recognition

Working memory neural networks, called Sustained Temporal Order REcurrent (STORE) models, encode the invariant temporal order of sequential events in short-term memory (STM). Inputs to the networks may be presented with widely differing growth rates, amplitudes, durations, and interstimulus intervals without altering the stored STM representation. The STORE temporal order code is designed to enable groupings of the stored events to be stably learned and remembered in real time, even as new events perturb the system. Such invariance and stability properties are needed in neural architectures which self-organize learned codes for variable-rate speech perception, sensory-motor planning, or 3-D visual object recognition. Using such a working memory, a self-organizing architecture for invariant 3-D visual object recognition is described. The new model is based on a model of Seibert and Waxman, which builds a 3-D representation of an object from a temporally ordered sequence of its 2-D aspect graphs. The new model, called an ARTSTORE model, consists of the following cascade of processing modules: Invariant Preprocessor → ART 2 → STORE Model → ART 2 → Outstar Network. [2, 3]

(B) Working Memories for Storage and Recall of Arbitrary Temporal Sequences

An extension of the STORE model encodes a working memory capable of storing and recalling arbitrary temporal sequences of events, including repeated items. The memory encodes the invariant temporal order of sequential events that may be presented at widely differing speeds, durations, and interstimulus intervals. This temporal order code is designed to enable all possible groupings of sequential events to be stably learned and remembered in real time, even as new events perturb the system. [4]

6. ADAPTIVE TIMING

(A) A Neural Network Model of Adaptively Timed Reinforcement Learning and Hippocampal Dynamics

A new neural network models adaptively timed reinforcement learning. The adaptive timing circuit is suggested to exist in the hippocampus, and to involve convergence of dentate granule cells on CA3 pyramidal cells, and NMDA receptors. This circuit forms part of a model neural system for the coordinated control of recognition learning, reinforcement learning, and motor learning, whose properties clarify how an animal can learn to acquire a delayed reward. Behavioral and neural data are summarized in support of each processing stage of the system. The relevant anatomical sites are in thalamus, neocortex, hippocampus, hypothalamus, amygdala, and cerebellum. Cerebellar influences on motor learning are distinguished from hippocampal influences on adaptive timing of reinforcement learning. The model simulates how damage to the hippocampal formation disrupts adaptive timing, eliminates attentional blocking, and causes symptoms of medial temporal amnesia. Properties of learned expectations, attentional focussing, memory search, and orienting reactions to novel events are used to analyse the blocking and amnesia data. The model also suggests how normal acquisition of subcortical emotional conditioning can occur after cortical ablation, even though extinction of emotional conditioning is retarded by cortical ablation. The model simulates how increasing the duration of an unconditioned stimulus increases the amplitude of emotional conditioning, but does not change adaptive timing; and how an increase in the intensity of a conditioned stimulus "speeds up the clock," but an increase in the intensity of an unconditioned stimulus does not. Computer simulations of the model fit parametric conditioning data, including a Weber law property and an inverted U property. Both primary and secondary adaptively timed conditioning are simulated, as are data concerning conditioning using multiple interstimulus intervals (ISIs), gradually or abruptly changing ISIs, partial reinforcement, and multiple stimuli that lead to time-averaging of responses. Neurobiologically testable predictions are made to facilitate further tests of the model. [39]

7. ADAPTIVE CONTROL

(A) Neural Representations for Sensory-Motor Control: Head-Centered 3-D Target Positions from Opponent Eye Commands

This project describes how corollary discharges from outflow eye movement commands can be transformed by two stages of opponent neural processing into a head-centered representation of 3-D target position. This representation implicitly defines a cyclopean coordinate system whose variables approximate the binocular vergence and spherical horizontal and vertical angles with respect to the observer's head. Various psychophysical data concerning binocular distance perception and reaching behavior are clarified by this representation. The representation provides a foundation for learning head-centered and body-centered invariant representations of both foveated and non-foveated 3-D target positions. It also enables a solution to be developed of the classical motor equivalence problem, whereby many different joint configurations of a redundant manipulator can all be used to realize a desired trajectory in 3-D space. [34]

(B) Emergence of Tri-Phasic Muscle Activation from the Nonlinear Interactions of Central and Spinal Neural Network Circuits

The origin of the tri-phasic burst pattern, observed in the EMGs of opponent muscles during rapid self-terminated movements, has been controversial. Computer simulations show that the pattern emerges from interactions between a central neural trajectory controller (VITE circuit) and a peripheral neuromuscular force controller (FLETE circuit). Both neural models have been derived from simple functional constraints that have led to principled explanations of a wide variety of behavioral and neurobiological data, including the generation of tri-phasic bursts. [5]

(C) Dynamic Programming for Optimal Control of Set-Up Scheduling with Neural Network Modifications

An optimal control soluation to change of machine set-up scheduling is demonstrated. The model is based on dynamic programming average cost per stage value iteration as set forth by Caramanis *et al.* for the 2D case. The difficulty with the optimal approach lies in the explosive computational growth of the resulting solution. A method of reducing the computational complexity is developed using ideas from biology and neural networks. A real-time controller is described that uses a linear-log representation of state space, with neural networks employed to fit cost surfaces. [1]